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Robust High Resolution Image from the Low Resolution Satellite Image

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Abstract— **In this paper, we propose a framework detecting and locating the land cover classes from a low-resolution image, which can play a very important role in the satellite surveillance image from the MODIS data. The lands cover classes by constructing super-resolution images from the MODIS data. The highest resolution of the MODIS images is 250 meters per pixel. By magnifying and de-blurring the low-resolution satellite image through the kernel regression. SR reconstruction is image interpolation that has been used to increase the size of a single image. The SRKR algorithm takes a single low-resolution image and generates a de-blurred high-resolution image. We perform bi-cubic interpolation on the input low-resolution image (LR) with a desired scaling factor. Finally, the KR model is then used to generate the de-blurred HR image. K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem, which generates a specific number of disjoint, flat (non-hierarchical) clusters. K-means clustering is employ in order to compare MODIS data and recognize land cover type, i.e., "Forest", "Land", "sea", and "Ice".**

Index Terms— **Satellite LR Image, Super-Resolution Image, MODIS Data**

I. INTRODUCTION

MODIS (Moderate Resolution Imaging Spectroradiometer) is playing a vital role in the development of validated, global, interactive Earth system models able to predict global change accurately enough to assist policy makers in making sound decisions concerning the protection of our environment. Many products have been developed from MODIS data. MODIS Level 2 products are distributed through a variety of the Atmosphere and Land products. From this Modes data, a Satellite image of land covering oceans, trees, hills and many more is being taken and that is being used for processing.

The aim of super-resolution (SR) is to generate a higher resolution image from lower resolution images. The need for high resolution is common in computer vision application for better performance in pattern recognition and analysis of images. High resolution is of importance in medical imaging for diagnosis. Many applications require zooming of a specific area of interest in the image wherein high resolution becomes essential, e.g. surveillance, forensic and satellite imaging application. The high resolution images are not available. This is since the setup for high resolution imaging proves expensive and also it may not always be feasible due to the inherent limitations of the sensor, optics manufacturing technology. These problems can be overcome through the use of image processing algorithms, which are relatively inexpensive, giving rise to concept of super resolution .it provides an advantage as it may cost less and the existing low resolution imaging system can still be utilized. An example of a low resolution images have been shown in the figure 1.

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Land cover is defined as the layer of soils and biomass, including natural vegetation, crops and human structures that cover the land surface [14]. It is less than 100 meters. Hence, the highest resolution of the MODIS data at 250 meters can potentially limit the applications of the MODIS data for land class detection.
Inspired by these advances on super-resolution technology, we propose a Kernel regression based super-resolution algorithm (SRKR). The SRKR only uses a single low resolution image as the input and generates a higher resolution image by learning a de-blurring process when down-sampling. Then we apply the SRKR to synthesize the high resolution MODIS image from its original low resolution version, 250m per pixel. The constructed super-resolution image can achieve 4 to 8 times higher resolution, which can potentially avoid the resolution limitation on land activity detection in the satellite image.

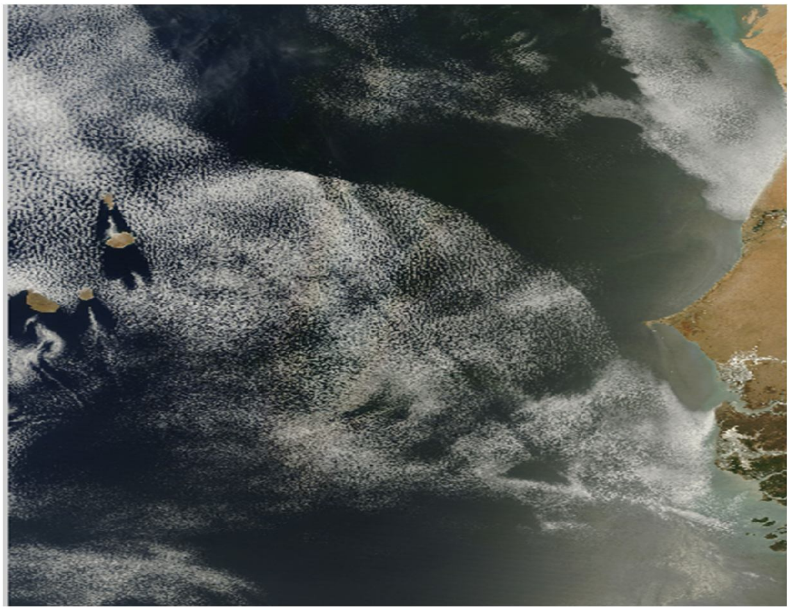


Figure 1: Low Resolution image from Satellite Image

The ground truth of land cover type at each selected geo-location is labeled by observing Google Earth, and verified in the MODIS images that these selected locations. Single frame super resolution, image up-sampling, or image interpolation is the process by which a single low resolution image is expanded spatially to a higher resolution image the relationship between high-resolution pixels and low-resolution pixels. The surface reflectance at the pixels range to consider the maximum range from the super-resolution MODIS image predict land cover type for a geo-location specified by latitude and longitude.

II. Related Work

In [1], a learning-based super-resolution algorithm has been implemented; a multi-resolution wavelet approach is adopted to perform the synthesis of local high-frequency features. To obtain a high-resolution image, wavelet coefficients of two dominant LH- and HL-bands are estimated based on wavelet frames. It utilizes the LH-band and transposed HL-band. The high resolution image is reconstructed via the wavelet transform.
Image enlargement can be done by using a simple interpolation technique. However, this approach cannot provide details in lines, edges, corners, and texture regions. Recently, there are several attempts for learning-based SR [5-8]. In [1] a learning-based SR algorithm based upon a wavelet synthesis approach. The relationship between an HR image and its LR image is closely correlated with the relationship between an image and its LL-band in the discrete wavelet transform (DWT) structure. In order to reconstruct an HR image, high bands of LH, HL, and HH are needed. The SR system consists of two basic processes, namely a training process and a synthesis process. In the training process, it saves an LR patch with its corresponding HR patch that contains fine details as a training set. In the synthesis process the first step is, SR is to decompose an input LR image into each band by using the DWF. It then estimates the LH- and HL- bands

for an HR image by using the training database. Note that the HL-band is estimated after transposing it so that it may use the same training database as in the LH-band. For HR image reconstruction, it uses an input LR image as the LL band. Since an LR image patch can be regarded as a patch in the LL-band of the DWT structure, and it use the inverse DWT (IDWT) for HR image reconstruction. For the IDWT operation, it perform sub-sampling after estimating the whole LH- and HL-bands.

In [2], the edge-directed interpolation algorithm for natural images had been implemented. The basic idea is to first estimate local covariance coefficients from a low-resolution image and then use these covariance estimates to adapt the interpolation at a higher resolution based on the geometric duality between the low-resolution covariance and the high-resolution covariance. Resolution enhancement of grayscale images and reconstruction of color images from CCD samples. Simulation results demonstrate that our new interpolation algorithm substantially improves the subjective quality of the interpolated images over conventional linear interpolation [9, 10].

Image interpolation concentrates on the problem of generating a high-resolution image from its low-resolution version. The model employed to describe the relationship between high-resolution pixels and low-resolution pixels plays the critical role in the performance of an interpolation algorithm. Conventional linear interpolation schemes (e.g., bilinear and bi-cubic) based on space-invariant models fail to capture the fast evolving statistics around edges and consequently produce interpolated images with blurred edges and annoying artifacts. Linear interpolation is generally preferred not for the performance but for computational simplicity.

The principal challenge of developing a multi resolution covariance based adaptation method is how to obtain the high-resolution covariance from the available low-resolution image. The optimal minimum mean squared error (MMSE) interpolation can be easily derived by modeling the image as a locally stationary Gaussian process. It is generally agreed that peak signal-to-noise ratio (PSNR) does not always provide an accurate measure of the visual quality for natural images except in the case that the only source of degradation is additive white noise. The improvements brought by new edge-directed interpolation over linear interpolation can often be easily observed when the interpolated images are viewed at a normal distance [11].

We assume that the low-resolution image $x_{i,j}$ of size H*W directly comes from of size of 2H*2W, i.e., $Y_{2i,2} = X_{i,j}$. The edge-directed property of covariance-based adaptation comes from its ability to tune the interpolation coefficients to match an arbitrarily-oriented step edge. When the scale of edges introduced by the distance between adjacent edges becomes comparable to the sampling distance, the aliasing components significantly overlap with the original components and might introduce phantom dominant linear features in the frequency domain. Such phenomena will not affect the visual quality of the interpolated image but will affect its fidelity to the original image.

The principal drawback with covariance-based adaptive interpolation is its prohibitive computational complexity. Since the computation of the activity measure is typically negligible when compared to that of covariance estimation, dramatic reduction of complexity can be achieved for images containing a small fraction of edge pixels. In [2] the authors have found that the percentage of edge pixels ranges from 5% to 15% for the test images used in our experiments, which implies a speed-up factor of 7–20.

The new edge-directed interpolation algorithm [2] can be used to magnify the size of a grayscale image by any factor that is a power of two along each dimension. In the first set of experiments with grayscale images, it uses the luminance components of the four color images. The new edge-directed interpolation is compared with two conventional linear interpolation methods: bilinear and bi-cubic. The low-resolution image (with the size of 384 * 256) is obtained by direct down-sampling the original image by a factor of two along each dimension (aliasing is introduced).

In [3], applied the Vegetative Cover Conversion (VCC) algorithms based on MODIS 250m radiance data to detect land cover changes caused by human activities or extreme natural events. Specifically, they used the MODIS images to detect wild fires, deforestation and floods, *etc*. Their experiments show that MODIS imaging is effective when significantly large portion of land cover is changed.

The Vegetative Cover Conversion (VCC) product is designed to serve as a global alarm for land cover change caused by anthropogenic activities and extreme natural events. MODIS 250 m surface reflectance data availability was limited both spatially and temporally in the first year after launch due to processing system constraints. To address this situation, the VCC algorithms were applied to available MODIS 250 m Level 1B radiance data to test the VCC change detection algorithms presented in this paper. Five data sets of MODIS Level 1B 250 m data were collected for the year 2000, representing: (1) Idaho–Montana wildfires; (2) the Cerro Grande prescribed fire in New Mexico; (3) flood in Cambodia; (4) Thailand–Laos flood retreat;

and (5) deforestation in southern Brazil. Decision trees are developed for each of the VCC change detection methods for each of these cases.

In [4], Mineral dust interacts with radiation and impacts both the regional and global climate. The retrieval of aerosol properties over land, including deserts, using the Moderate Resolution Imaging Spectroradiometer Deep Blue algorithm makes the first direct characterization of the origin of individual sources possible. Four years of data from the eastern part of West Africa, which includes one of the most active natural dust sources and the highest population density on the continent, are processed. Sources are identified on the basis of the persistence of significant aerosol optical depth from freshly emitted dust, and the origin is characterized as natural or anthropogenic on the basis of a land use data set.

It combines land use data set and direct satellite measurements to identify natural and anthropogenic dust sources. It selects a domain to include a very intense natural sources and a country with high population density. Level 2 MODIS Deep Blue (MODIS DB) products and the domain selection before presenting our methodology to locate natural and anthropogenic dust sources and comparing with other studies. Then we attempt to quantify the importance of anthropogenic sources relative to natural sources.

III. Method Overview:

The goal of super-resolution (SR) is to estimate a high resolution (HR) image from one or a set of low-resolution (LR) satellite images. The figure 2 shows about the process of method used in this paper.LR satellite image process takes the image from MODIS data or any other sources e.g. Google Earth images in which the resolution of image is low.

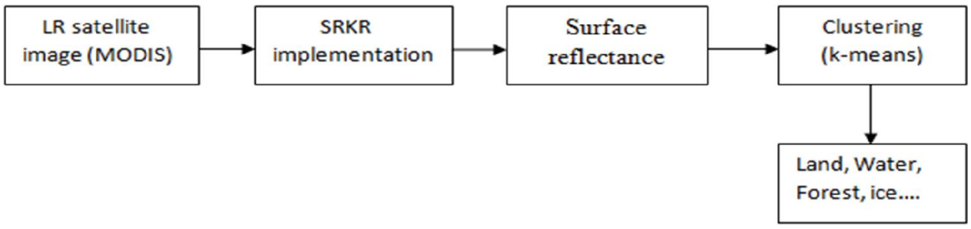


Figure 2: Flowchart to evaluate the feasibility of land cover class activities detections using the SRKR super-resolution algorithm

IV. Super Resolution Image Using Interpolation And Kernel Regression:

Classical parametric image processing methods rely on a specific model of the signal of interest and seek to compute the parameters of this model in the presence of noise. Examples of this approach are presented in diverse problems ranging from de-noising to up-scaling and interpolation. A generative model based upon the estimated parameters is then produced as the best estimate of the underlying signal.

In contrast to the parametric methods, nonparametric methods rely on the data itself to dictate the structure of the model, in which case this implicit model is referred to as a regression function. The relatively recent emergence of machine learning methods, kernel methods have become well-known and used frequently for pattern detection and discrimination problems. Surprisingly, it appears that the corresponding ideas in nonparametric estimation are not widely recognized or used in the image and video processing literature. Indeed, in the last decade, several concepts related to the general theory we promote here have been rediscovered in different guises, and presented under different names such as normalized convolution, bilateral filter, edge-directed interpolation, and moving least squares. We shall say more about some of these concepts and their relation to the general regression theory.

We develop a super-resolution algorithm based on the Kernel regression, SRKR to magnify and de-blur the 250m resolution MODIS images. The SRKR algorithm follows the super-resolution algorithm proposed, except that we adopt the Kernel regression (KR) instead of the Gaussian process regression [12]. The SRKR algorithm takes a single low resolution image and generates a de-blurred high resolution image. The constructed super-resolution image can achieve 4 to 8 time's higher resolution as compared to the original 250m resolution. Hence, super-resolution images can provide more details on identification of land classes from the satellite image.

Image interpolation is a process that estimates a set of unknown pixels from a set of known pixels in an image. It has been widely adopted in a variety of applications, such as resolution enhancement [13].

Interpolation is a method of constructing new data points within the range of a discrete set of known data points. A different problem which is closely related to interpolation is the approximation of a complicated function by a simple function and Up-sampling is the process of increasing the sampling rate of a signal.
The SRKR algorithm consists of two major steps: (a) up-sampling and (b) de-blurred as shown in Figure 3(a). In the up-sampling step , we perform bi-cubic interpolation on the input low resolution image (LR) with a desired scaling factor. Then partition both low resolution image and the interpolated high resolution image into corresponding pixels. After performing the Kernel Regression (KR) on the obtained targets and the feature vectors, we obtain the KR model. The KR model is then used to predict the blurred high resolution (HR) image using the bi-cubically interpolated high resolution image as its input feature vector.
In the de-blurring step, we further blur and down-sample the blurred HR image to obtain the blurred LR image. Similar to the up-sampling step, the blurred HR image, the blurred LR image, and the original LR image are partitioned into pixels as shown in Figure 3(b). For each pixel of the original LR image, we sample pixels as the training targets, and the neighbor pixels in the corresponding blurred LR patch as the feature vector for each sampled pixel. We perform the KR regression and obtain the KR model, which has modeled the de-blurring process at low resolution. The KRR model is then used to predict the de-blurred HR image using the neighbor pixels of the blurred HR image.

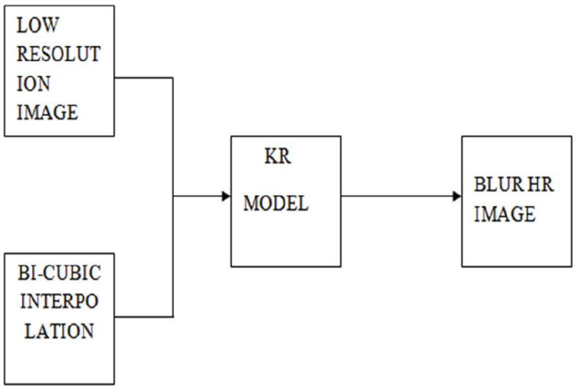


Figure 3 (a)

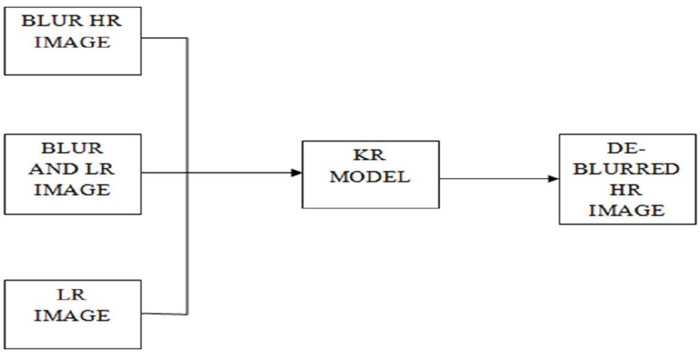


Figure 3 (b)
Figure 3: Flowchart of the SRKR super-resolution algorithm in two steps: (a) up-sampling and (b) De-blurring

V . SURFACE REFLECTANCE:

The Land Surface Reflectance Science Computing Facility is responsible for producing the MODIS Surface Reflectance product (MOD09). MODIS Surface Reflectance is a seven-band product computed from the MODIS Level 1B land bands 1, 2, 3, 4, 5, 6, and 7. The product is an estimate of the surface spectral reflectance for each band as it would have been measured at ground level as if there were no atmospheric scattering or absorption. It corrects for the effects of atmospheric gases, aerosols, thin cirrus clouds and is a

major input utilized in the generation of several land products such as Vegetation Indices, BRDF, Land Cover, Snow Cover, Thermal Anomalies and LAI/FPAR.
For each selected pixel, we extract surface reflectance of a patch in the super-resolution MODIS data. The pixel intensity in the patch is sensitive to rotation change and noise data. Hence we propose to use a statistic based feature representation. The maximum pixel range to classify the land cover types is taken from MODIS data.

VI . Clustering Based Land Cover Type Classification:

K-means [15] is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters fixed a priori values. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and grouping is done.
K-Means clustering generates a specific number of disjoint, flat (non-hierarchical) clusters. It is well suited to generating globular clusters. It is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The maximum pixel range to classify "Forest", "Land", "sea", and "Ice" land cover types according to the surface reflectance of the MODIS data.

VII. Experimental Results:

The Experimental results mainly focus on super resolution (e.g., blurred, noisy) from one single low resolution input image. In practical, low resolution images are generated by smoothing and down-sampling target scenes with low quality image sensors. The task of recovering the original high resolution (HR) image from a single low resolution (LR) input is an inverse problem of this generation procedure.
One criterion of solving this inverse problem is to minimize the reconstruction error. In other words, the result which can produce the same low resolution image as the input one is preferred. Kernel regression is proposed to minimize the reconstruction error efficiently by an SRKR algorithm. However, since a lot of information is lost in the generation process, this problem is severely underdetermined. There might be multiple solutions to minimize this error, even for multiple LR input images.

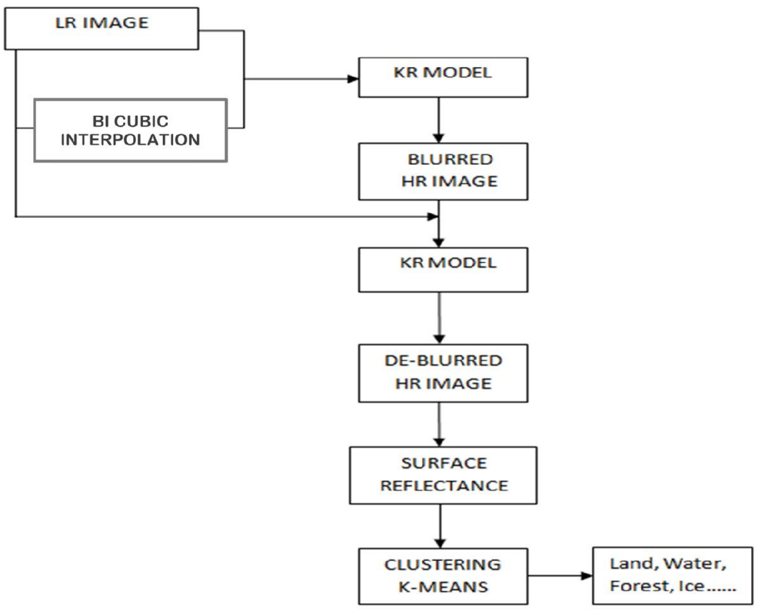


Figure 4: Architecture of Super-resolution through the SRKR algorithm

Figure 4 shows the architecture of Super-resolution through the SRKR algorithm then we develop a super-resolution algorithm based on the Kernel regression, i.e., SRKR, to magnify and de-blur the 250m resolution MODIS images. The SRKR algorithm takes a single low resolution image and generates a de-blurred high resolution image. The constructed super-resolution image can achieve 4 to 8 time's higher resolution as compared to the original 250m resolution. Hence, super-resolution images can provide more details on identification of land cover classes in the MODIS Image. The maximum pixel range to classify "Forest", "Land", "sea", and "Ice" land cover types according to the surface reflectance of the MODIS data.

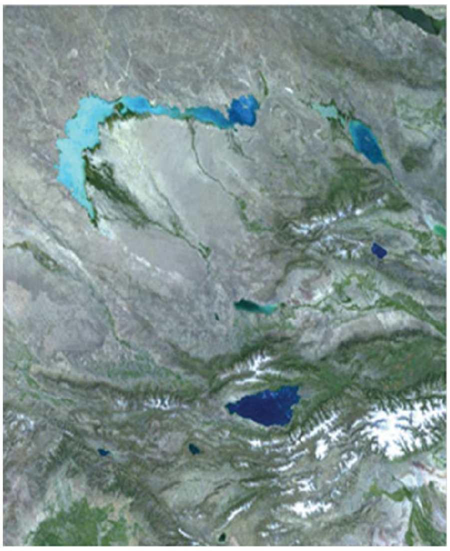
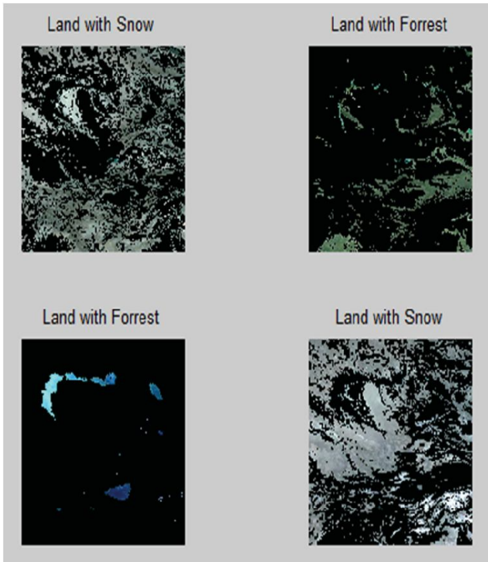


Figure 5(a)

(b)



(c)

Figure 5: Super-resolution through the SRKR algorithm: (a) original Low Resolution image (b) Clustered Image (Black, white, Gray) (c) Resulted HR Image.

Figure 5(a) shows the original Low resolution MODIS image. Figure 5(b) and 5(c) show its high resolution clustered image which result the super-resolution images obtained from the SRKR algorithm shows more details on edges or coast lines, where land class detections often occur. However, as the scaling factor

increases to 4, the super-resolution MODIS image is not showing continuous improvement from the visual inspection.

VIII. Conclusion And Future Work

In this paper, we have proposed a super-resolution algorithm using the Kernel Regression which is a popular non-parametric fitting technique. We have studied the feasibility of applying the SRKR super-resolution algorithm on an image. A Low Resolution image to High Resolution image by using SRKR with a clustered image formed then predicts the land cover classes efficiently within the range.

In future work, the work can be moved in identifying the changes in forest area before and after they are burnt or deforestation has occurred.

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